Object-based land use/land cover change detection of a coastal city using Multi-Source Imagery: a case study of Lagos, Nigeria

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Abstract

In the wake of the burgeoning population, socio-economic and environmental issues facing coastal areas, LULC change detection has become an essential tool for environmental monitoring towards achieving sustainable development. In this study, an object-based image analysis approach using post-classification comparison technique was applied for assessing the LULC of the coastal city of Lagos from 1986 to 2016. The study describes how satellite imagery from different sources (Landsat and SENTINEL 2A) can be successfully integrated for Land use Land cover change detection. The results show that between 1986 and 2016, there were net increases in bare areas, built-up areas, and shrublands and a general decline in forestlands, waterbodies and wetlands. Over 60,000ha cover (approx. 190% increase) was converted into built-up areas while 83,541ha (835.4km^2) of forestland were lost, suggesting high rates of urbanization and corresponding deforestation. About 60% loss of wetlands was also observed in the same time period. The decrease in water bodies and a steady increase in bare and built-up areas are possibly due to the prevalent land reclamation activities in the study area. Higher rates of deforestation and increase in bare areas were observed from 2001 to 2016 in comparison to 1986 to 2001. The observed trends are likely to continue, and for future management actions, predictive studies are suggested to provide more empirical evidence.

Keywords: *Object-based image analysis classification, GEOBIA, Lagos, Land Use Land cover, coastal urbanization, post-classification comparison technique, Change detection*

1. Introduction

The land use-land cover (LULC) of the earth's surface has been experiencing temporal and spatial changes since time immemorial, and the trend is likely to continue in the future (Giri 2012). Global population increase, coupled with technological developments suggest that LULC changes are not likely to decline, hence, there are needs to keep developing new techniques for monitoring LULC changes. One of the goals of land change monitoring is to provide a better understanding of the interactions and relationships between humans and the environment for the purpose of sustainable development (Lu, Mausel, Brondízio, & Moran, 2004). Remote sensing offers a quick, timely and cheap method of acquiring up-to-date data over large areas of land including areas inaccessible through direct field surveys. Hence, a considerable number of studies has gone into the LULC change assessment of coastal areas over temporal and spatial scales using different imagery types and change detection techniques including the use of multi-source data (Adepoju, Millington, & Tansey, 2006; El-Hattab, 2016; Okude & Ademiluyi, 2006; Wang, Sousa, & Gong, 2004). It has been noted that as data become more accessible at higher spatial and temporal resolutions, the application of multi-source data for change detection will grow into a key area of research (Giri, 2012; Lu et al., 2004).

Two broad image analyses types used for change detection are the pixel-based or object-based analyses. Differences between the pixel and object-based methodologies are highlighted in literature (Blaschke et al., 2014; Xie et al., 2016). The pixel-based approach is based on spectral characteristics of single pixels such as DN values and variance while, the building blocks of the Object-based image analysis (OBIA) are polygons (Weih & Riggan, 2010). The polygons, also known as image objects, are not single pixels but rather a group of pixels sharing common characteristics like spectral signatures and contexts (Pathak, 2014). The argument of OBIA is that semantic information necessary for accurate interpretation of images such as shape, texture and contextual information are not represented in single pixels but in meaningful image objects called segments/polygons (Blaschke, 2010; Blaschke et al., 2014). In recent times, OBIA is more specifically referred to as Geographic Object-based image analysis (GEOBIA) as a sub-discipline in GIScience (Hay & Castilla, 2008). Although OBIA is known for high-resolution images, the definition for resolution is contextual and is more correctly expressed as H or L resolution where H-resolution implies a case where objects in a scene are much bigger than the pixel resolutions and hence, the radiance for a single object may be represented by several pixels while the L resolution means the opposite (Blaschke et al., 2014). Hence, OBIA is not restricted to high-resolution images alone as an L-resolution case can change into an H-resolution case if "Legends" of the scene are more generalized, thereby increasing the size of scene objects (Blaschke et al., 2014). On these bases, several studies have used different image types ranging from high-resolution images like IKONOs (0 -2m) and SPOT (2 – 4m) to medium resolution images like Landsat 8 (10m) and Landsat TM and ETM+ (30m) (Aslami & Ghorbani, 2018; Chubey, Franklin, & Wulder, 2006; Dimitrakopoulos et al., 2010; Phiri & Morgenroth, 2017). OBIA incorporates spatial information into the classification procedure using two main steps; image segmentation and image classification (Blaschke, 2010; Blaschke et al., 2014; Wang et al., 2004). The image segmentation process involves grouping pixels with similar characteristics into polygons (image objects or segments) until the entire imagery is represented by a network of these polygons which form the basis for the subsequent image analysis and classification (Blaschke et al., 2014). Several studies have shown the superiority of *OBIA* over pixel-based classifiers for H resolution images where higher accuracies are obtained (Aslami & Ghorbani, 2018; Blaschke et al., 2014; Gao & Mas, 2008; Geoffrey J. Hay, Castilla, Wulder, & Ruiz, 2005; Huth et al., 2012; Trang, Toan, Ai, Giang, & Hoa, 2016; van der Sande, de Jong, & de Roo, 2003; Wang et al., 2004). Besides accuracy, OBIA has also been found to overcome the challenge specialists refer to as *salt and pepper* effect (Blaschke, 2010).

Different change detection algorithms have been developed and documented for quantifying changes in LULC. Lu *et al.,* (2004) provide a detailed overview of these change detection techniques. Some of these change detection algorithms include Mono-temporal change detection, Composite analysis, Image differencing, change vector analysis and post-classification technique (Pathak, 2014). The post-classification comparison technique also known as the *map-to-map comparison* is the comparative analysis of classification maps produced independently from different dates (Serra, Pons, & Saurí, 2003). It has been observed to be particularly suitable for detecting LULC changes on a multi-temporal scale (Coppin et al., 2004; Giri, 2012). Similarly, as this technique enables the classification of two or more dates of imagery independently, it reduces the challenge associated with radiometric calibration between dates (Coppin et al., 2004).

The coastal city of Lagos, a major commercial and technological hub in the West African region and the continent at large is one of the three megacities currently in Africa and the most populous city on the continent. In spite of its status, existing scientific studies on its spatial changes are sparse and lack temporal coherence mainly due to the challenge of obtaining usable cloud-free data from a single source over relatively long, evenly spaced timespans. For instance, to obtain the full image of the study area for a discrete period, images from three contiguous grids need to be mosaicked. Acquiring, usable data from a single source for all three grids over certain intervals of decades is usually problematic or near-impossible. This study addresses this challenge by 1) exploring the use of multi-source data (Landsat and SENTINEL) thereby increasing data source options; 2) utilizing the merits of the OBIA for achieving high classification accuracy; 3) adopting the map-to-map comparison for change detection. Hence, the study focuses on the LULC change detection of Lagos, Nigeria at an equal interval of 15 years from 1986 to 2001 to 2016, thereby setting a uniform trend for possible subsequent LULC change studies in the study area. Ultimately, the use of free multi-source satellite imagery, demonstrated by this study and the findings can help scientists, planners and policymakers identify and manage the evolution of LULC better for sustainability in Lagos. Other researchers can also evaluate the methodology, especially in the use of SENTINEL 2A data in other study areas.

2. Materials and Methods

2.1. Description of the study area

Lagos, a fast-rising megacity in south-west Nigeria is located at latitude 6027’11” N and Longitude 3023’45” E of the globe with a coastline length about 180km bordering the Atlantic Ocean. The entire area coverage is over 3,550km^2 and besides the presence of a large Lagoon and other waterbodies, the land cover range from heavily urbanized built-up areas to forested areas. The urban agglomeration which makes up 37% of the total land area accommodates over 80% of the entire population (Nwagwu & Oni, 2015) but the LULC of the previously sub-urban areas are rapidly changing due to population increase. For instance, the urban agglomeration had a population of 2.6million in 1980, but by 2000, it had risen to 7.3m and it currently stands at 13.9 million in 2019 (UNDESA, 2019). This drastic population growth is bound to affect the LULC dynamics of the study area. Figure 1 represents the study area's map.

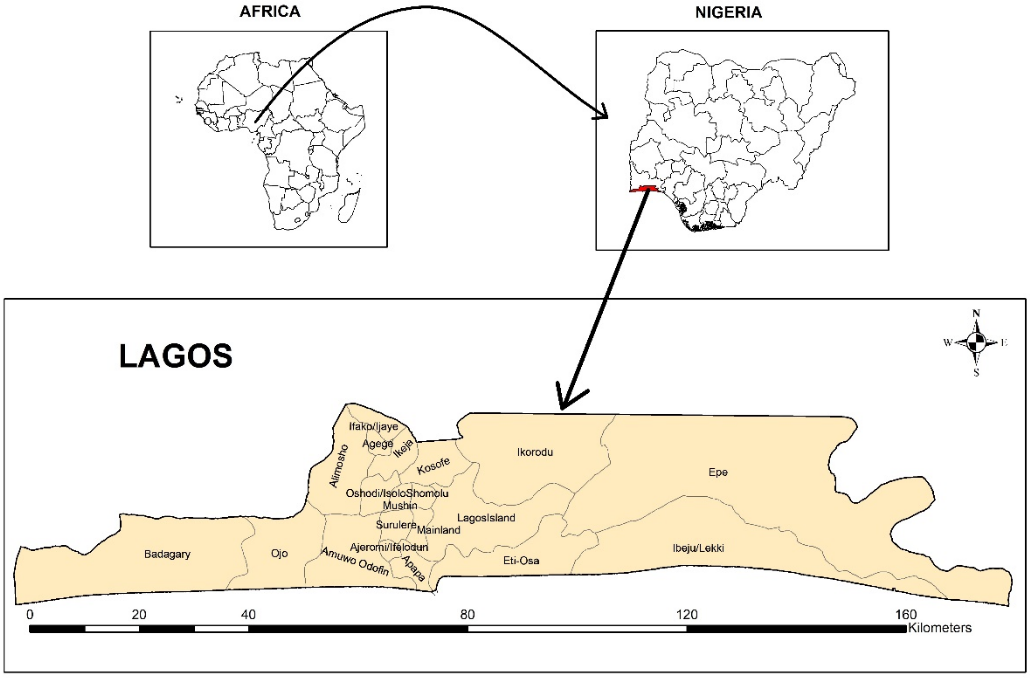

Figure 1: Map of the study area

2.2. Image acquisition and Pre-processing

Landsat 4-5 (TM), Landsat7 ETM+ and SENTINEL 2A images were acquired based on the availability of cloud-free images at 15-year intervals for the years 1986, 2001 and 2016 respectively. The study area cuts across three grids, comprising Path/Row; 190/056, 191/055 and 191/056 on Landsat, and T31NDH, T31NEH, and T31NFH on SENTINEL 2A grid system. Table 1 summarizes the details of the acquired data.

Table 1: Satellite images acquired for the study

Year	Landsat Grid (Path/Row)			Bands	Spectral range (µm)	Spatial Resolutions (m)
	190/056	191/55	191/56			
1986	15 Jan.	22 Jan.	11 March	2, 3, 4	0.52–0.60, 0.63–0.69, 0.76–0.90	30
2001	17 Feb.	09 Dec.	09 Dec	2, 3, 4	0.52–0.60, 0.63–0.69, 0.77–0.90	30
	SENTINEL 2A (Path/Row)					
	T31NDH	T31NEH	T31NFH			
2016	7 Jan.	7 Jan.	7 January	3, 4, 8	0.56, 0.665, 0.842	10

Source: United States Geological Survey (USGS); European Space Agency (ESA)

2.3. Land Change Monitoring

The three broad steps involved in change detection projects as highlighted in Lu *et al.*, (2004); 1) Image preprocessing; 2) Selection of the suitable change detection analysis technique; 3) Accuracy assessment were followed in this study. In addition to that, a multi-source data integration was carried out on the datasets (Table 1) as shown in Figure 2.

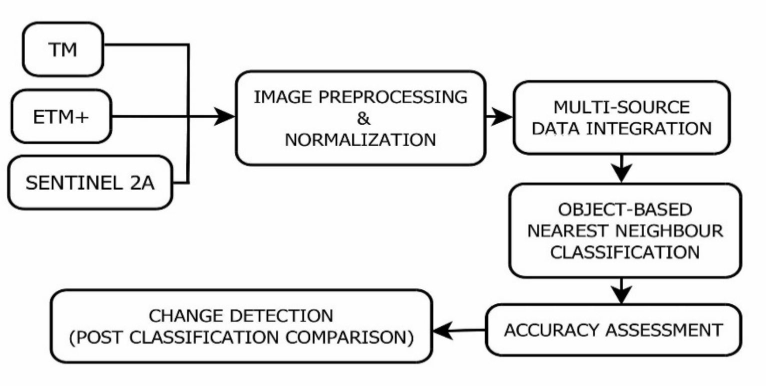

Figure 2: Methodology Flowchart developed for this study

2.3.1. Image preprocessing and normalization

The Landsat images were passed through three image preprocesses - image normalization (radiometric normalization and atmospheric correction), haze reduction and layer stacking of the images. Radiometric normalization reduces the differences in mosaics resulting from uneven acquisition time or date (Helmer, 2010). The atmospheric correction and haze reduction help reduce image noises such as particles in the atmosphere during image transmission and acquisition (Janzen, Fredeen, & Wheate, 2006). The layer-stacked multi-spectral images for each year were mosaicked and clipped using the shapefile of the study area obtained from (DIVA-GIS). The SENTINEL 2A dataset was preprocessed using the Sentinel Application Platform (SNAP) as detailed on the European Space Agency's website (Geo University, 2018). The image preprocessing of the SENTINEL comprised image display handling such as compositing, raster band filtering and subsetting, and resampling. At the end of the image preprocessing, image normalization and layer stacking for all the images were done on the ENVI 3.5 software.

2.3.2. Multi-source data Integration

Blaschke et al., (2014) notes that OBIA is not only context-aware but more importantly, it is multisource capable. One of the major challenges inherent in the use of data from different sources for land change classification is how to normalize the images and achieve a basis for equitable image comparison. Several studies have approached this challenge differently. However, Petit and Lambin, (2001) identified three parameters for the interpretation and classification of multi-source data. They are highlighted as "the thematic content of the maps' legends, the level of generalization, and the spatial resolutions of the maps. In the same vein, Serra, Pons, & Saurí, (2003) suggested some points to consider when using post-classification change detection for multi-source data. Two main considerations were ensuring high overall accuracies and resampling the layers into similar pixel sizes and origins. For the accuracy assessment, their study suggested multiplying the accuracies of the individual maps or the use of error matrices developed by Congalton & Green, (2009). Although Serra, Pons, & Saurí, (2003)'s study suggested resizing images with the finer resolutions into the coarser ones, it was observed in this study that this might not always be plausible if the LULC classes are broadly classified and if OBIA which favours finer resolution images are being considered as seen in this study. Based on the observations, care was taken to ensure comparable legends and harmonized spatial resolutions for all the maps before the image classifications. Firstly, six LULC classes were identified using levels 1 and 2 of the CORINE classification nomenclature (Kosztra, Büttner, Hazeu, & Arnold, 2017), although some modifications were made based on location-specific considerations. For instance, *bare area*s include areas mostly covered by sand with no green vegetation *e.g.* beaches and reclaimed lands; *Forestlands* are areas over 0.5ha characterized by dense tree cover higher than 5m and canopy cover greater than 10% (FAO, 2001); *Shrublands* are areas dominated by low lying plants including grasses, shrubs and herbs, with few scattered trees. Hence, the six LULC classes include; Bare Areas, Built-Up Areas, Forestlands, Shrublands, Waterbodies and Wetlands. These LULC classes formed the basis for the classification of all the maps. Secondly, the spatial resolutions of the images were harmonized by equalizing the levels of thematic content and spatial details. The bands for LULC in the SENTINEL 2A are in 10m resolution while that of the Landsat are in 30m. The variations in the pixels' spectral contents due to resolution differences prompted the use of OBIA. Therefore, the spatial resolutions of the LULC bands with the equivalent spectral ranges in Landsat (as shown in Table 3) were resampled into the 10m resolution based on the nearest neighbour analysis. Band harmonization in multi-source data use for LULC analyses are extensively discussed by Millward et al., (2006).

2.3.3. Object-based Image Analysis

Details on the OBIA segmentation and classification adopted in this study can be found in Blaschke et al., (2014). The adopted OBIA methodology proceeds through the following stages; multi-resolution segmentation, identifying homogenous features and selecting the image objects, and assigning classes to the objects. The latter two steps constitute the image classification stage of the OBIA. Multi-resolution segmentation aggregates spatial information into groups of homogenous pixels called objects at different (multi) scales. These objects represent actual features like rivers, wetlands etc. in the image and they were digitized manually. This technique, also referred to as the *region merging technique,* is further detailed in Baatz & Schape, (2000). The pixel homogeneity – in terms of texture, colour, tone, shape, size and context- was fully considered during the image classification. The identification of the features, selecting and assigning classes to the objects were done for each map. The detailed nature of this segmentation process ensured thorough and simultaneous reference checks with the high-resolution images on google earth and the permanent landmarks identified within the study area. Over 100 reference points were obtained for the analysis of each map. Its downside is, it is highly labour-intensive and relies on expert knowledge (Blaschke, 2010). In subsequent studies, a supervised or rule-based OBIA with the use of software like eCognition is highly recommended. By the end of this stage, the six LULC classes had been assigned to the image objects of each map.

2.3.4. Accuracy Assessment

A point-based random stratified sampling design well detailed in (Congalton & Green, 2009; Congalton, 1991; Garson, 2012) was used to obtain 200 validation points for each map. Google earth high-resolution satellite images have been found valuable for classifications and accuracy assessments especially when they are combined with ground-truthing (Giri, 2012). Hence, 100 reference points were picked during a ground-truthing exercise based on the criteria outlined in Aslami & Ghorbani, (2018). The criteria include; sample unit ≥ 90m × 90m in size, the area is visually and spectrally homogenous, and the heterogeneity (variability) between units in the area is maximum. The identified landmark reference points in addition to the google earth images corresponding to each dataset were used to verify the accuracies of the maps. The sampling design was systematic and ensured an equitable representation of all parts of the study area and the corresponding land use classes. Finally, based on Congalton and Green (2009), multivariate techniques such as error matrix, kappa coefficient of agreement, producers and users accuracy and overall accuracy were applied for the accuracy assessment.

2.3.5. Change detection using post-classification comparison

The post-classification comparison technique was adopted due to its simplicity and reasons also identified by El-Hattab, (2016) which is, besides providing information on the size and distribution of changed areas, it provides information on the other LULC contributing to the change in each LULC both in discrete values and percentages. After the image classification and accuracy assessment of each map, the post-classification change detection process involved the area computations for the classified and validated images of each year which were then compared starting with the most recent classification. Further details on the use of post-classification change detection for multi-source data are detailed in Serra, Pons, & Saurí, (2003). The change detection, visualization and intersect analysis of the three maps were done using the ArcGIS 10.3 software.

3. Results

The results obtained from the accuracy assessment, classification and change detection and are highlighted and discussed in this section.

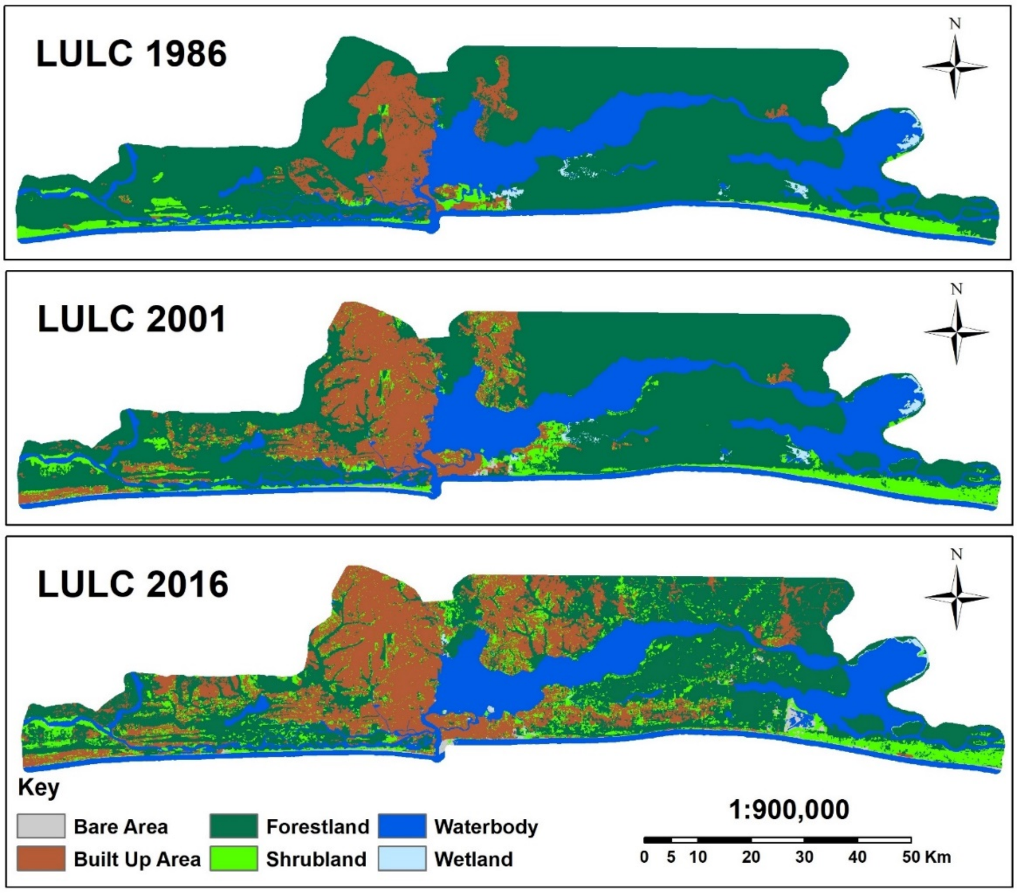

Figure 3: The Land Use Land cover map of Lagos in 1986; 2001 and 2016.

3.1. Accuracy assessment

The summary of the accuracy assessment results is presented in Table 2. The results show high overall classification accuracies of 83.5, 85.5 and 87.5 and equally high kappa statistics of 0.78, 0.80 and 0.85 for the years 1986, 2001, and 2016, respectively. These findings further demonstrate the effectiveness of the OBIA as Ma et al., (2017) notes that studies using the OBIA approach achieve mean classification accuracies of over 80%.

Table 2: Summary of the accuracy assessment results

LULC CLASSES	1986		2001		2016	
	[1]PA(%)	[2]UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Bare Area	91.67	84.62	100.00	75.00	100.00	95.24
Built Up Area	86.36	95.00	90.32	96.55	90.70	88.64
Forestland	88.46	84.15	84.78	92.86	71.70	95.00
Shrubland	60.00	78.26	75.00	61.54	82.34	68.29
Waterbody	100.00	77.55	96.55	87.50	100.00	97.67
Wetland	60.00	92.31	76.92	83.33	100.00	72.73
Overall Accuracy	**83.50**		**85.50**		**87.50**	
Kappa Statistics	**0.78**		**0.80**		**0.845**	

[1] = Producers accuracy; [2] = User's accuracy

3.2. Change detection

Table 3 represents the statistics of the land cover changes in each interval and the summary of the coverage and distribution of the LULC in the study area from 1986 to 2016.

Table 3: Changes in the LULC classes and the summary of coverage distribution

a. **1986 - 2001**

LULC Classes	1986 area (Ha)	2001 area (Ha)	Change in area (Ha)	Change % from original area
Bare Area	627	1,424	797	**127**
Built Up Area	32,199	59,879	27,679	**86.0**
Forestland	227,390	189,427	-37,964	**-16.7**
Shrubland	13,654	24,376	10,722	**78.5**
Waterbody	81,622	80,773	-849	**-1.0**
Wetland	2,236	1,850	-386	**-17.3**

b. **2001 - 2016**

LULC Classes	2001 area (Ha)	2016 area (Ha)	Change in area (Ha)	Change % from original area
Bare Area	1,424	3,313	1,889	**132.7**
Built Up Area	59,879	93,113	33,235	**55.5**
Forestland	189,427	143,849	-45,578	**-24.1**
Shrubland	24,376	36,915	12,539	**51.4**
Waterbody	80,773	79,648	-1,126	**-1.4**
Wetland	1,850	890	-960	**-51.9**

c. 1986 - 2016

LULC Classes	1986 area (Ha)	2016 area (Ha)	Change in area (Ha)	Change % from original area
Bare Area	627	3,313	2,686	**428.2**
Built Up Area	32,199	93,113	60,914	**189.2**
Forestland	227,390	143,849	-83,541	**-36.7**
Shrubland	13,654	36,915	23,261	**170.4**
Waterbody	81,622	79,648	-1,974	**-2.4**
Wetland	2,236	890	-1,345	**-60.2**

d. Summary (Coverage distribution)

LULC Classes	AREA IN Hectares					
	LULC_1986	% of Total	LULC_2001	% of Total	LULC_2016	% of Total
Bare Area	627	**0.2**	1,424	**0.4**	3,313	**0.9**
Built Up Area	32,199	**9.0**	59,879	**16.7**	93,113	**26.0**
Forestland	227,390	**63.6**	189,427	**53.0**	143,849	**40.2**
Shrubland	13,654	**3.8**	24,376	**6.8**	36,915	**10.3**
Waterbody	81,622	**22.8**	80,773	**22.6**	79,648	**22.3**
Wetland	2,236	**0.6**	1,850	**0.5**	890	**0.2**
TOTAL	**357,728**	**100**	**357,728**	**100**	**357,728**	**100**

The LULC map for each year is represented in Figure 3. A cursory look at Figure 3 reveals that there is an increase in the bare/built-up areas and the gradual loss of forest cover. Overall, the combination of waterbodies and forestlands constitute the largest percentage of the land cover in the study area but they both show decreasing trends over the years (Table 3, Figure 3). Forestland cover shows declines from 63.6% to 53% to 40.2% while waterbodies declined slightly from 22.8% to 22.6% to 22.3% between 1986 and 2016. Wetland cover also declined steadily from 0.6% cover in 1986 to 0.2% in 2016, the larger loss occurring between 2001 and 2016 (Table 3d). Conversely, built-up and bare areas experienced unprecedented increases from 9% to 16.7% to 26% and 0.2 to 0.4 to 0.9, respectively. Noticeable increases were also observed for shrublands in the period under study.

4. Discussion

As observed in the results, the changes over the 30-year period include notable increases in bare areas, built-up areas, and shrublands, a rapid decline in forestlands, and wetlands and slight changes in waterbodies. The increase in bare areas was higher between 2001 - 2016 than 1986 - 2001 and this may likely be due to increased land reclamation activities (Idowu & Home, 2015) in the former. A typical example is the Eco-Atlantic – a 9km^2 land reclamation project which started in 2008 (Eko Atlantic, 2012). Previous studies on the land cover change dynamics of the study area lend credence to the general findings of this study. For instance, an unsupervised pixel-based classification study on LULC changes between 1984 and 2006 in the study area by Obiefuna *et al.,* (2013), showed an exponential increase in bare areas, built-up areas, swamps and mangroves (wetlands) and a slight decrease in waterbodies over the 24-year period. They ascribed these changes to rapid urbanization and land reclamation. Taiwo (2009)'s study on the coastal part (Eti-Osa) of the study area over a 28-year period from 1978 to 2006 showed a 19% loss in wetlands in that region. Other studies have employed varying approaches and different timelines but the general observation common to all the studies is that the built-up areas increased drastically from the 1980s to the 2000s and the trend has continued beyond 2010s (Adepoju, Millington and Tansey, 2006; Okude and Ademiluyi, 2006; Olaleye and Abiodun, 2009; Nwokoro and Dekolo, 2011; Nkwunonwo, 2013; Ukor, Ogbole and Alaga, 2016). Some of the studies attempted to use multi-source data in their classifications; Landsat and SPOT (Adepoju et al., 2006; Okude & Ademiluyi, 2006), Topo-maps and Quick bird images (Olaleye & Abiodun, 2009). Also, most of the studies only focused on the metropolitan part of the study area (Adepoju et al., 2006; Nkwunonwo, 2013; Nwokoro & Dekolo, 2011; Olaleye & Abiodun, 2009; Ukor et al., 2016). The inconsistencies in the legends, spans of time considered and spatial extents of these studies make a harmonious detailed conclusion from all the studies a challenge. The most recent and advanced of the study is the one done by Akinluyi *et al.,* (2018) which focused on changes in the shorelines between 1984 and 2016 and the associated land cover change using the Landsat TM, ETM+ and OLI datasets. The study reported an increase in built-up area coverage from 12.2 to 36.2% between 1984 and 2015, in comparison to the increase from 9% to 26% between 1986 and 2016 reported in this study. The relatively higher values in the built-up areas in the former are likely because no distinction was made between built-up and bare areas and areas considered as shrublands in the current study could have been classified as built-up areas in the former. A pixel-based supervised classification was used for the image analysis in Akinluyi *et al.,* (2018)'s study, while this study employed the OBIA classification approach due to its advantages of obtaining a higher classification accuracy (Ma et al., 2017).

5. Conclusion

This study focused on the LULC change detection of the coastal city of Lagos over a multi-temporal scale spanning 1986, 2001 and 2016. Landsat and SENTINEL datasets were successfully integrated in the study. Object-based image analysis approach using a post-classification comparison technique was found efficient, yielding overall accuracies of 87.5%, 85.5%, 83.5% and kappa statistics of 0.845, 0.80, 0.78 for 2016, 2001 and 1986 maps respectively. The results show there were net increases in bare areas, built-up areas, and shrublands and a general decline in forestlands, waterbodies and wetlands between 1986 and 2016. Overall, a high rate of urbanization and corresponding deforestation were observed and these are likely due to the drastic population increase. The rate of deforestation and urbanization was higher from 2001 to 2016 in comparison to 1986 to 2001. These trends are likely to continue, hence predictive studies are recommended while the use of supervised or rule-based image segmentation will simplify the classifications in the future.

6. References

Adepoju, M. O., Millington, A. C., & Tansey, K. T. (2006). Land use/land cover change detection in metropolitan lagos (Nigeria): 1984-2002. *ASPRS 2006 Annual Conference*, 7. Retrieved from http://www.asprs.org/a/publications/proceedings/reno2006/0002.pdf

Akinluyi, F. O., Adebola, A. O., & Adeseko, A. A. (2018). Assessment of Shoreline and Associated Landuse/Land cover Changes along Part of Lagos Coastline, Nigeria. *Contemporary Trends in Geoscience*, *7*(1), 59–70. https://doi.org/10.2478/ctg-2018-0004

Aslami, F., & Ghorbani, A. (2018). Object-based land-use/land-cover change detection using Landsat imagery: a case study of Ardabil, Namin, and Nir counties in northwest Iran. *Environmental Monitoring and Assessment*, *190*(7). https://doi.org/10.1007/s10661-018-6751-y

Baatz, M., & Schape, A. (2000). Multiresolution Segmentation: An Optimization Approach for High Quality Multi-Scale Image Segmentation. In J. Strobl, T. Blaschke, & G. Griesbner (Eds.), *Angewandte Geographische Informations-Verarbeitung* (pp. 12–23). Karlsruhe, Germany: Wichmann Verlag.

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, *65*(1), 2–16. https://doi.org/10.1016/j.isprsjprs.2009.06.004

Blaschke, Thomas, Hay, G. J., Kelly, M., Lang, S., Hofmann, P., Addink, E., … Tiede, D. (2014). Geographic Object-Based Image Analysis - Towards a new paradigm. *ISPRS Journal of Photogrammetry and Remote Sensing*, *87*, 180–191. https://doi.org/10.1016/j.isprsjprs.2013.09.014

Chubey, M. S., Franklin, S. E., & Wulder, M. A. (2006). Object-based Analysis of Ikonos-2 Imagery for Extraction of Forest Inventory Parameters. *Photogrammetric Engineering & Remote Sensing*. https://doi.org/10.14358/pers.72.4.383

Congalton, R G, & Green, K. (2009). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. *The Photogrammetric Record* (Vol. 2). https://doi.org/10.1111/j.1477-9730.2010.00574_2.x

Congalton, Russell G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, *37*(1), 35–46. https://doi.org/10.1016/0034-4257(91)90048-B

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., & Lambin, E. (2004). Review ArticleDigital change detection methods in ecosystem monitoring: a review. *International Journal of Remote Sensing*, *25*(9), 1565–1596. https://doi.org/10.1080/0143116031000101675

Dimitrakopoulos, K., Gitas, I. Z., Polychronaki, A., Katagis, T., & Minakou, C. (2010). Land Cover / Use Mapping Using Object Based Classification of SPOT Imagery. *Remote Sensing for Science, Education, and Natural and Cultural Heritage*, 263–271.

DIVA-GIS. (2016). Shapefile of the administrative boundary of Lagos, Nigeria. Retrieved August 20, 2016, from http://www.diva-gis.org/datadown

Eko Atlantic. (2012). *Eko Atlantic- The new Gateway to Africa*. Retrieved from https://www.ekoatlantic.com/wp-content/uploads/2015/08/EKOATLANTIC_Broch_2012.pdf

El-Hattab, M. M. (2016). Applying post classification change detection technique to monitor an Egyptian coastal zone (Abu Qir Bay). *Egyptian Journal of Remote Sensing and Space Science*, *19*(1), 23–36. https://doi.org/10.1016/j.ejrs.2016.02.002

FAO. (2001). *Global Forest Resources Assessments 2000 Main Report*. Rome.

Gao, Y., & Mas, J. (2008). A comparison of the performance of pixel based and object based classifications over images with various spatial resolutions. *Online Journal of Earth Sciences*, *2*(8701), 27–35. https://doi.org/doi:ojesci.2008.27.35

Garson D. (2012). *Sampling*. NC 27205 USA: Statistical Associates publishing.

Geo University. (2018). ESA Sentinel Application Platform Tutorial. Retrieved from https://www.geo.university/courses/tutorial-to-esa-snap-software

Giri, C. P. (2012). Remote sensing of land use and land cover: principles and applications. *ICRC Press*, *1161*(August), 1–469. https://doi.org/10.1080/01431161.2014.891560

Hay, G.J., & Castilla, G. (2008). Geographic Object-Based Image Analysis (GEOBIA): a new name for a new discipline. In T. Blaschke, S. Lang, & G. Hay (Eds.), *Object- Based Image Analysis.* (pp. 75–89). Heidelberg, Berlin, New York: Springer.

Hay, Geoffrey J., Castilla, G., Wulder, M. A., & Ruiz, J. R. (2005). An automated object-based approach for the multiscale image segmentation of forest scenes. *International Journal of Applied Earth Observation and Geoinformation*, *7*(4), 339–359. https://doi.org/10.1016/j.jag.2005.06.005

Helmer, E. H. (2010). Radiometric Normalization : Encyclopedia of Geography. *Sage-Ereference*, *75*(2001), 1–2. Retrieved from http://www.sage-ereference.com/geography/Print_n953.html

Huth, J., Kuenzer, C., Wehrmann, T., Gebhardt, S., Tuan, V. Q., & Dech, S. (2012). Land cover and land use classification with TWOPAC: Towards automated processing for pixel- and object-based image classification. *Remote Sensing*, *4*(9), 2530–2553. https://doi.org/10.3390/rs4092530

Idowu, T. E., & Home, P. G. (2015). Probable Effects of Sea Level Rise and Land Reclamation Activities on Coastlines and Wetlands. In *The 2015 JKUAT Scientific Conference* (pp. 207–220). Nairobi: JKUAT. Retrieved from http://journals.jkuat.ac.ke/index.php/jscp/article/view/1251/1028

Janzen, D. T., Fredeen, A. L., & Wheate, R. D. (2006). Radiometric correction techniques and accuracy assessment for Landsat TM data in remote forested regions. *Canadian Journal of Remote Sensing*, *32*(5), 330–340. https://doi.org/10.5589/m06-028

Kosztra, B., Büttner, G., Hazeu, G., & Arnold, S. (2017). *Updated Corine Land Cover illustrated nomenclature guidelines*. Austria. Retrieved from https://land.copernicus.eu/user-corner/technical-library/corine-land-cover-nomenclature-guidelines/docs/pdf/CLC2018_Nomenclature_illustrated_guide_20190510.pdf

Lu, D., Mausel, P., Brondízio, E., & Moran, E. (2004). Change detection techniques. *International Journal of Remote Sensing*, *25*(12), 2365–2407. https://doi.org/10.1080/0143116031000139863

Ma, L., Li, M., Ma, X., Cheng, L., Du, P., & Liu, Y. (2017). A review of supervised object-based land-cover image classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *130*, 277–293. https://doi.org/10.1016/j.isprsjprs.2017.06.001

Millward, a a, Piwowar, J. M., & Howarth, P. J. (2006). Time-series analysis of medium-resolution, multisensor satellite data for identifying landscape change. *Photogrammetric Engineering and Remote Sensing*, *72*, 653–663.

Nkwunonwo, U. C. (2013). Land use/Land cover mapping of the Lagos Metropolis of Nigeria using 2012 SLC-off Landsata ETM+ Satellite Images. *International Journal of Scientific & Engineering Research*, *4*(11), 1217–1223.

Nwagwu, I., & Oni, T. (2015). Lagos and Its Potentials for Economic Growth. Retrieved November 27, 2017, from https://ng.boell.org/2015/07/02/lagos-and-its-potentials-economic-growth

Nwokoro, I. I. C., & Dekolo, S. O. (2011). Land use change and environmental sustainability: The case of Lagos Metropolis. *WIT Transactions on Ecology and the Environment*, *155*, 157–167. https://doi.org/10.2495/SC120141

Obiefuna, J. N., Nwilo, P. C., Atagbaza, A. O., & Okolie, C. J. (2013). Land Cover Dynamics Associated with the Spatial Changes in the Wetlands of Lagos/Lekki Lagoon System of Lagos, Nigeria. *Journal of Coastal Research*, *288*, 671–679. https://doi.org/10.2112/JCOASTRES-D-12-00038.1

Okude, A. S., & Ademiluyi, I. A. (2006). Implications of the Changing Pattern of Landcover of the Lagos Coastal Area of Nigeria. *American-Eurasian Journal of Scientific Research*, *1*(1), 31–37. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.520.1371&rep=rep1&type=pdf

Olaleye, J. B., & Abiodun, O. E. (2009). Land Use Change Detection and Analysis Using Remotely Sensed Data in Lekki Peninsula Area of Lagos , Nigeria Land Use Change Detection and Analysis Using Remotely Sensed Data in Lekki Peninsula Area of Lagos , Nigeria. *Area*, 3–8.

Pathak, S. (2014). New Change Detection Techniques to monitor land cover dynamics in mine environment. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *40*(8), 875–879. https://doi.org/10.5194/isprsarchives-XL-8-875-2014

Petit, C. C., & Lambin, E. F. (2001). Integration of multi-source remote sensing data for land cover change detection. *International Journal of Geographical Information Science*, *15*(8), 785–803. https://doi.org/10.1080/13658810110074483

Phiri, D., & Morgenroth, J. (2017). Developments in Landsat land cover classification methods: A review. *Remote Sensing*. https://doi.org/10.3390/rs9090967

Serra, P., Pons, X., & Saurí, D. (2003). Post-classification change detection with data from different sensors: Some accuracy considerations. *International Journal of Remote Sensing*, *24*(16), 3311–3340. https://doi.org/10.1080/0143116021000021189

Taiwo, O. J. (2009). A Spatial Temporal Analysis of Wetland Losses in the Lagos Coastal Region, Southwestern Nigeria, Using Multi-Date Satellite Imagery. In *IEEE Geoscience and Remote Sensing Society Conference* (pp. 928–930). Capetown: IGARSS.

Trang, N. T. Q., Toan, L. Q., Ai, T. T. H., Giang, N. V., & Hoa, P. V. (2016). Object-Based vs. Pixel-Based Classification of Mangrove Forest Mapping in Vien An Dong Commune, Ngoc Hien District, Ca Mau Province Using VNREDSat-1 Images. *Advances in Remote Sensing*, *05*(04), 284–295. https://doi.org/10.4236/ars.2016.54022

Ukor, C. D., Ogbole, J., & Alaga, A. . (2016). Analysis of Land Use Land Cover Change in Ikeja, Lagose State. Nigeria Using Remote Sensing and Gis Techniques. *International Journal of Science and Technology*, *5*(10), 462–472.

UNDESA. (2019). *Historical population for Lagos Agglomeration*. Retrieved from https://population.un.org/wup/

van der Sande, C. J., de Jong, S. M., & de Roo, A. P. J. (2003). A segmentation and classification approach of IKONOS-2 imagery for land cover mapping to assist flood risk and flood damage assessment. *International Journal of Applied Earth Observation and Geoinformation*, *4*(3), 217–229. https://doi.org/10.1016/S0303-2434(03)00003-5

Wang, L., Sousa, W. P., & Gong, P. (2004). Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery. *International Journal of Remote Sensing*, *25*(24), 5655–5668. https://doi.org/10.1080/014311602331291215

Weih, R. C., & Riggan, N. D. (2010). Object-based classification vs. pixel-based classification: Comparitive importance of multi-resolution imagery. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XXXVIII*, 1–6.

Xie, Z., Shi, R., Zhu, L., Peng, S., & Chen, X. (2016). Comparison of Pixel-Based and Object-Oriented Land Cover Change Detection Methods. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLI-B7*(July), 579–583. https://doi.org/10.5194/isprsarchives-XLI-B7-579-2016